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Productivity, Efficiency, and Managerial Performance Regress and Gains in United States Universities: A Data Envelopment Analysis

G. Thomas Sav[1]

Abstract

This paper uses data envelopment analysis to investigate the extent to which universities in the United States have undergone productivity and efficiency changes, partly due to managerial performance, during the 2005-09 academic years. Using panel data for 133 research and doctoral universities, the focus is on the primary drivers of U.S. publicly controlled higher education. DEA efficiency and returns to scale estimates are provided. In addition, university total factor productivity changes via the Malmquist index are decomposed into component parts. Results suggest that U.S. universities experienced average productivity regress. On an annual basis such was present prior to the global financial crisis. However, productivity gains appeared in concert with the crisis. Managerial efficiency tended to hamper productivity gains but, on the positive side, showed slight improvements over time. Decreasing returns to scale prevailed but from a policy perspective a return to economy wide growth may automatically correct some over production.

JEL classification numbers: I21, I22, I23, L3, C6
Keywords: Data Envelopment, Productivity, Efficiency, Manage, Universities

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[1] Department of Economics, Raj Soin College of Business, Wright State University, Dayton, OH, USA, e-mail: tom.sav@wright.edu

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1 Introduction

The purpose of this paper is to estimate the productivity, efficiency, and possible managerial performance changes that have unfolded among research and doctoral granting universities in the United States. Panel data is employed for 133 public universities covering four academic years, 2005-2009. Data envelopment analysis (DEA) is used to estimate university efficiencies and associated returns to scale. Taking full advantage of the panel structure, changes in university productivities are provided via the Malmquist index and are decomposed into technological advances, scale effects, and managerial decision-making.

As a mathematical programming approach, DEA has become the standard nonparametric tool for evaluating the efficiency performance of individual producers. It is due to the seminal work of Charnes, et al. (1978) and has wide applications to any collection of „decision making units" or DMUs. It has been applied to government agencies, for-profit firms, and not-for-profit entities, including educational institutions (Cooper, et al., 2004). In the present inquiry, the university serves as the DMU. The basic methodology determines, for every DMU, a set of universities that perform as a composite and efficient unit that is "best" and can be used as an efficiency benchmark. A university under evaluation is inefficient, for example, if the benchmark uses less input to produce the same output or produces more output with the same input. Efficiency scores are produced and range from 0 to 1 with the latter being a 100% efficient DMU. With panel data observations, productivity changes over time can be explored using the Malmquist (1953) index defined by Caves et al. (1982). Indexes below unity represent productivity regress while those above unity demonstrate productivity improvements. Moreover, total productivity changes can be decomposed into that part which is due to technical changes, size or scale efficiency changes, and changes that can be attributed to management.

The paper is motivated by the fact that public universities in the U.S., as well as internationally, have come under increased scrutiny regarding the efficiency with which they deliver their educational products. Pressures to improve university operating efficiencies parallel the more general but widespread call for public management reforms accelerated by the global financial crisis. Deficit driven reductions in the provision of publicly provided goods and services have brought and will likely continue to bring greater demands for increased efficiency in the management and delivery of all governmentally provided goods, including public higher education. Using four academic years of the most recently available data for research and doctoral granting universities, the efficiency estimates and productivity changes provided herein are representative of those which exist among the primary drivers of public higher education in the U.S. The analysis covers academic years 2005-09 and, therefore, includes both the relative calm and economic growth associated with the pre-financial crisis years and the economic turmoil years of the so-called Great Recession. Thus, the results offer some insights into the potential effects of the financial crisis on university productivity, efficiency, and management responses. A literature search suggests that the research is the first to apply DEA analysis in a panel data framework to U.S. universities.

The next section of the paper proceeds with a review of the DEA literature as applied to higher education in an international context. That is followed by an account of the DEA and Malmquist methodology employed in the paper, a data explanation section, a section pertaining to the empirical results, and a final section containing the concluding remarks.

2 DEA Applications

The interest of this paper lies in the application of DEA to higher education. Applications to many industries and some lower levels of education along with an historical development of DEA are well documented elsewhere, e.g., Cooper (2004), Cook and Zhu (2008), and Johnes (2004). With regard to higher education, the bulk of literature is relatively new and undersized in comparison to the totality of DEA applications. However, it is international in scope, spanning nine countries. The level of analysis is of two varieties. On one hand, DEA has been used in investigating the efficiency and comparisons of individual departments or programs within a university. On the other hand, it has been applied at the firm level in researching the efficiency of universities within a country. In the first case, the department or program is the DMU. In the second case, the university is the DMU. Empirically, the majority of studies uses cross sectional data, providing efficiency estimates for a single academic year. There appears to be only three studies that have utilized panel data in exploring university efficiency and productivity changes over time.

Table 1 provides a summary of existing studies organized in chronological order according to these foci. For the cross sectional studies, Table 1 reports the range of DEA efficiency estimates. Efficiency scores are relative to the best practice units that achieve efficiency scores of 1.0. For the panel data studies, the total factor productivity ranges (Malmquist indexes) are summarized. Scores below unity indicate a productivity regress while those above one measure productivity advances. Due to the wide variation in the reporting of empirical results among all these studies, the range became the best common denominator for summary and comparative purposes.

At the departmental level, Beasley (1990) examines the efficiency of chemistry and physics departments within 52 United Kingdom universities in the 1986 (i.e., 1986-87) academic year. In an extended model, the same data is used in the Beasley (1995) study. In contrast, Stern, et al. (1994) concentrate on a single university, Ben Gurion, in 1988 and apply DEA to 21 different departments.

Table 1: DEA Applications to Higher Education

Study	Country or University	Academic Year(s)	Universities (Departments)	Efficiency Range
Cross Section Department Level				
Beasley (1990)	U.K.	1986	52 (2)	0.42-1.0
Stern, et al. (1994)	Ben-Gurion	1988	1 (21)	0.35-1.0
Beasley (1995)	UK	1986	52 (2)	0.32-1.0
Cobert et al. (2000)	U.S.	1997	24 (24)	0.92-1.0
Korhonen et al. (2001)	Helsinki Sch	1996	1 (18)	0.23-1.0
Reichmann (2004)	U.S.	1998	118 (118)	0.68-1.0
Casu & Thanassoulis (2006)	U.K.	1999	108 (108)	0.32-1.0
Leitner et al. (2007)	Austria	2000 2001	12 (958) 12 (953)	0.18-1.0
Cross Section University Level				
Ahn et al. (1988)	U.S.	1984	161	0.64-1.0
Breu et al. (1994)	U.S.	1992	25	0.87-1.0
Athanassapoulos & Shale (1997)	U.K.	1992	52	0.37-1.0
Avkiran (2001)	Australian	1995	36	0.82-1.0
Glass et al. (2006)	U.K.	1996	98	0.14-1.0
McMillan & Chan (2006)	Canada	1992	45	0.55-1.0
Panel Data University Level				
Castano & Cabanda (2007)	Philippines	1999-2003	59	0.928-1.299
Worthington & Lee (2008)	Australia	1998-2003	35	0.98-1.130
Agasisti & Johnes (2009)	Italy England	2001-04	57 127	1.094 1.085

The study by Cobert, et al. (2000) is a 1997 cross section of 24 MBA programs in United States. Other investigations include a sample of 18 research units at the Helsinki school of economics (Korhonen, et al., 2001), 118 university libraries in the U.S., the efficiency of the central administration in 108 United

Kingdom universities (Casu and Thanassoulis, 2006), and more than 950 departments housed in 12 Austrian universities in both 2000-01 and 2001-02 academic years. Given the diversity of these studies, it is not surprising that there exists a wide range of efficiency estimates; overall from 0.18 to 0.92 for the minimum efficiency scores. As one would expect, a larger efficiency range occurs with potentially more heterogeneous units, e.g., the 950 departments undertaken in the Leitner, et al. (2007) Austrian study. Likewise, the smallest efficiency range occurs among the small sample of 24 MBA programs examined by Cobert, et al. (2000). The units therein would be highly homogeneous being that they were chosen as the top 24 ranked MBA programs in the United States.

Ahn, et al. (1988) provided the first DEA study in using the university as the DMU. The efficiency estimates pertain to 161 doctoral granting universities operating in the U.S. during the 1984-85 academic year. Shortly thereafter, Breu et al. (1994) selected the 25 top ranked national universities in the United States. As in the departmental results, the more selective and homogeneous is the sample, the smaller tends to be the range of efficiency scores. In this case, the Ahn, et al. (1988) minimum university level efficiency is 64% while the Breu et al. (1994) least efficient university operates at 87%. The two United Kingdom studies by Athannassapoulos and Shale (1997) and Glass, et al. (2006) and the Canadian university study provided by McMillan and Chan (2006) generate wider ranges in university efficiency scores when compared to those reported for the U.S. However, it should be noted that the low efficiency of 0.14 in the Glass et al. (2006) study is the minimum university efficiency reported for one DEA model among several exploratory models investigated in that study.

Clearly, the scarcer panel data studies represent the newer additions to this body of literature. Each study uses the benefit provided by panel data to estimate the university productivity changes over time via the Malmquist index. For the 59 Philippine universities analyzed over the five academic years 1999-2003, Castano and Cabanda (2007) report productivity regress and improvement in the Malmquist index range of 0.928 to 1.299. Not reported in Table 1, the Philippine mean productivity change was 1.002, i.e., a 0.2% average productivity growth. Over approximately the same academic years but for Australian universities, Worthington and Lee (2008) report productivity changes ranging from 0.98 to 1.13 with a mean annual productivity gain of 3.3%. The dual country study provided by Agasisti and Johnes (2009) covers a more recent period of four academic years, 2001-04 (i.e., 2001-02 through 2004-05), for 57 Italian and 127 English universities. The study did not provide index ranges and, therefore, Table 1 reports only the means for each country. Thus, in comparison to the sampled Philippine and Australian universities, there is, on average, greater productivity gains experienced among Italian and English universities; 9.4% per annum in Italy and 8.5% per annum in England.

Of course, at question must be the usefulness and validity of any serious comparative evaluations among the results of these studies. Given the variability in departments, programs, institutions, academic years, and higher education financing and regulatory environments across countries, it seems the wiser to accept these results as constituting a literature review rather than a mechanism for deriving any definitive inter-country conclusions. What is of importance to the present paper is the absence of any rigorous DEA study of U.S. university operating efficiencies since the 1992-93 academic year. Moreover, to date there has not been a longitudinal study of U.S. university productivity and efficiency changes employing the research advantages offered by a Malmquist DEA. The remainder of this paper proceeds to fill both gaps using U.S. panel data observations on research and doctoral universities in the U.S. over four academic years, 2005-09.

3 Methodology

In the context of DEA, a university's productivity or efficiency can be measured as performance in using inputs to produce outputs. For multiple outputs and inputs, the efficiency performance in ratio form is expressed as

$$\sum_{r=1}^{s} u_r y_{ro} / \sum_{i=1}^{m} v_i x_{io} \tag{1}$$

where the y_r outputs, r=1, … , s, and x_i inputs, i=1, … , m, are observed for the DMU or university under evaluation as denoted by the "o" subscript. The u and v represent variables defining the weights or relative importance of each output and input, respectively.

Assuming that universities seek to operate efficiently, the linear programming problem can be stated as an output-oriented envelopment model. That model follows the work of Agasisti and Johnes (2009). Some other studies, e.g., McMillan and Chan (2006) have used an input-oriented model but find that the results are generally insensitive to model selection. Many times, as presently, the selection is defined by the availability of data. Under a constant returns to scale technology, CRS, or CCR as due to Charnes, Cooper, and Rhodes (1978) the model can be specified using fairly standard notation (e.g., Cooper, et al., 2004 and Cook and Zhu, 2008) as

$$\max_{\phi,\lambda} \phi \tag{2}$$

subject to

$$\sum_{j=1}^{N} y_{rj}\lambda_j - \phi y_{ro} \geq 0 \qquad r = 1,\ldots,s \tag{3}$$

$$x_{io} - \sum_{j=1}^{N} x_{ij}\lambda_j \geq 0 \qquad i = 1,\ldots,m \tag{4}$$

$$\lambda_j \geq 0 \qquad j = 1,\ldots,N \tag{5}$$

where the λ are constants and the value of $1/\phi$ is the technical efficiency score of the *j*th university. Allowing for variable returns to scale, VRS, or BCC in reference to Banker, Charnes, and Cooper (1984), requires the addition that $\sum \lambda = 1$.

Efficiency scores range from zero to one and are based on comparisons among universities and the creation of a production frontier of both real and virtual universities. Constraint (3) above pertains to the outputs of the real and virtual university, whereas (2) imposes the input constraints. A university is deemed inefficient if its virtual comparison produces more efficiently. The "distance" from the frontier determines the efficiency score. Universities on frontier obtain efficiency scores equal to one in value and, therefore, are efficient.

Over time, universities can experience changes in their operating efficiencies given a fixed technology. In addition, there can occur technological changes that affect and shift the frontier. Combined, the two effects determine the total productivity change. When panel data is available, the Malmquist index (Malmquist, 1953) can be used to measure this productivity change and decompose it into its two separate components. Following Fare et al. (1994), the index is comprised of the distance (*D*) functions of productivity in year *t*+1 relative to year *t* and can be expressed (e.g., Cooper, et al., 2004 and Cook and Zhu, 2008) as follows:

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \right) \left(\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right) \right]^{\frac{1}{2}} \tag{6}$$

The first component of (6) measures the change in efficiency in year *t*+1 relative to year *t*, i.e., the relative distance (*D*) between actual and efficient production over the measured time. This technical efficiency for the CRS model can additionally be decomposed into a pure technical or management efficiency and scale efficiency. The second component is the geometric mean of two indices and measures the shift in the production frontier, i.e., using year *t*+1 technology compared to year *t* technology. If university productivity is increasing (decreasing), then the resulting index, *M*, will be greater than one (less than one). The total productivity change is zero when technological improvements are equally offset by deterioration in technical operating efficiencies of universities.

4 Data

Data for individual universities were acquired from the U.S. National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS). Periodic changes in the IPEDS reporting requirements alter the definition or availability of some variables and, therefore, impose difficulties in creating panel data sets. In the present study, it was possible to create a stable set of observations for Carnegie classified publicly controlled doctoral and research universities over the academic years 2005-06 through 2008-09. These universities represent the top tier of the U.S. system of publicly provided higher education. Given that universities receive the same Carnegie classification designation, the sample is likely to satisfy the homogeneity preferences of DEA. Upon removing universities that neglected to report any of the defined outputs, a balanced panel was created for 133 universities.

University outputs are largely based on the success of previous multiproduct research, beginning with the seminal work of Cohn, et al. (1989) and moving to subsequent investigations by Koshal and Koshal (1999), Sav (2004), and Lenton (2008), among others. Those parametric studies, along with the majority of DEA studies reviewed herein, specify models based on three outputs. Those outputs include undergraduate education, graduate education, and research. For educational output measures, most parametric studies have used some measure of student enrollments while most DEA studies have used degrees awarded.

As somewhat of a compromise, but most relevant to public universities in the U.S., the present measures follow that of Sav (2004) in using the full academic year of credit hour production as the output for both undergraduate and graduate education. Unlike enrollment measures, the credit hour output measure accounts for both part and full-time students carrying different course loads throughout the full academic year and includes any intersessions and summer terms. Moreover, it is consistent with the subsidy model under which public universities receive state supported revenues in return for credit hour production, not conferred degrees. In addition, conferred degrees would not adequately capture large credit hour or enrollment increases affecting university production during recessionary periods and the 2005-09 academic period under study in the present paper. In contrast, nearly all studies use the receipt of government and private research grants, gifts, and contracts as the research output. This proxy is widely accepted within the both the applied parametric and nonparametric literature and, in the absence of any reliable substitute, is grounded in the notion that external funding support correlates highly with university wide research output.

Five measures are employed for labor and capital inputs: three pertaining to labor and two are used for capital. Similar to Agasisti and Johnes (2009), Chakraborty and Poggio (2008), and Sav (2012), faculty remain the primary labor input. However, as with Sav (2012), IPEDS is used to separately account for teaching and research faculty compared to administrative faculty. Teaching and research faculty are defined as the number of faculty employed on nine month contracts. Administrative faculty are employed on twelve month contracts. Although it is recognized that teaching and research faculty perform some administrative tasks and vice versa, the division is used to define major labor responsibilities and subsequent resource allocations. For non-faculty labor input, the university's academic support expenditure is used. It would be preferred to use non-academic staff employed in various support functions and by professional and non-professional responsibilities, but such data was either not obtainable or did not exist in a consistent panel data framework.

For the two capital input measures, the value of equipment is used along with expenditures on auxiliary enterprises. While land values were available, they were subject to the volatility of local real estate markets and, therefore, rejected over the use of a more nationally priced capital input. The auxiliary enterprise expenditure also escapes that volatility but manages to capture the scope of university dormitories, food services, and sports arenas, all of which attract students and credit hour production.

Table 2 presents a summary of the variables and their means and standard deviations. All dollars are in real 2009 year dollars.

Table 2: University Academic Year Variable Means and Standard Deviations

Variable	Mean	Standard. Dev.
Undergraduate Education, Credit Hours	15952	8251
Graduate Education, Credit Hours	3815	2830
Research, Dollars	1.63E+08	1.78E+08
Teaching and Research Faculty, Number	783	391
Administrative Faculty, Number	164	170
Capital Equipment, Dollars	2.64E+08	2.63E+08
Academic Support, Dollars	5.35E+07	5.25E+07
Auxiliary Capital, Dollars	7.53E+07	6.95E+07

On average, graduate education comprises almost 20% of total credit hour production. Approximately 17% of total faculty input is allocated to administration. Salaries for administrative faculty are approximately 25% above that for teaching and research faculty. Given the capital input measures, capital equipment is more than three times that of the auxiliary input.

5 Results

University efficiency results for both the CRS and VRS models are presented in Table 3. For comparative purposes, the academic year 2005-06 is set with the 2008-09 academic year. In addition, efficiency estimates are provided for the full four years, 2005-09, as determined at the mean university outputs and inputs. Differences in CRS relative to VRS efficiencies are due to the scale inefficiency present in the CRS estimates, i.e., the CRS technical efficiency is the product of VRS technical efficiency and scale efficiency. Thus, Table 3 also reports the scale efficiency as determined by the ratio of CRS to VRS efficiencies.

Table 3: University DEA Efficiency Results

Academic Year(s)	2005-06			2008-09			2005-09 Means		
	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale
Mean	0.828	0.877	0.946	0.791	0.846	0.938	0.810	0.859	0.944
Median	0.804	0.914	0.980	0.763	0.847	0.968	0.789	0.866	0.978
Minimum	0.383	0.383	0.616	0.355	0.372	0.559	0.365	0.371	0.557
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Standard Dev.	0.138	0.132	0.078	0.150	0.149	0.079	0.142	0.138	0.075
Percent Efficient	27%	42%	32%	20%	33%	20%	22%	35%	24%
Decreasing Returns			50%			61%			62%
Constant Returns			32%			21%			24%
Increasing Returns			17%			18%			14%

In both the 2005-06 and 2008-09 academic years, mean university efficiencies under both CRS and VRS estimates are approximately 80% and better. However, there occurs a slight decline over the academic years. In part, the decline could be the effect of surprise adjustments driven by public higher education budget cuts and the simultaneous increase in enrollments, especially at the graduate level, that followed the global financial meltdown. Approximately 4.5% of the decline occurs on the CRS front as opposed to 3.5% for the VRS efficiency. Therefore, the scale efficiency decline is somewhat muted and exhibits an overall decline of only 0.8%. When institutions are evaluated at their four year mean outputs and inputs, both efficiency measures exceed 80% and the scale efficiency approaches 95%.

The least efficient university struggles to reach an efficiency score of 0.4 or 40%. But when the underlying data were examined, there were only four universities with efficiency measures falling below 50%. A tally on those falling below 75% efficiency is another matter. Under CRS, the number of universities below 75% efficiency increase from 39 in 2005-06 to 59 in 2008-09. Under VRS, that number increases from 21 to 37 universities. When evaluated at the mean outputs and inputs, universities falling below the 75% cut number 55 and 30 under the CRS and VRS, respectively. Subsequently, over time the percent of universities on the frontier and, therefore, efficient (maximum efficiency score of one) declines from 27% to 20% with CRS and from 42% to 33% with VRS in place. At the mean output and input vectors, the results suggest that there are

22% to 35 % of the universities that achieve maximum efficiency depending on the underlying returns to scale technology.

Table 3 also reports the percentage of universities operating under three different returns to scale: decreasing, constant, and increasing. That determination is the result of the comparison of technical efficiency under non-increasing returns to scale and under variable returns to scale (Coelli, 1996). In each of the academic years and at the mean outputs and inputs, at least half of the universities produce under decreasing returns to scale. Moreover, the 2005-06 to 2008-09 jump from 50% to 61% operating under decreasing returns is due to the decline in universities previously producing under constant returns to scale. Again, this could be attributed to the increased scale of production accompanying the recessionary increases in credit hour production. In contrast, there is much greater returns to scale stability among the smaller percentage of universities persistently operating in the range of increasing returns.

To better capture efficiency changes over time and take full advantage of the panel data, we turn to the Malmquist results presented in Table 4. The methodology extensions noted earlier are implanted in Table 4, viz., the 2005-09 Malmquist total factor productivity change is decomposed into technological change (frontier shifts) and technical efficiency change (CRS) with the latter being further separated into pure or managerial efficiency change (VRS) and scale efficiency change (CRS/VRS). In the lower portion of Table 4, the annual means provide further insights into the dynamics of change.

Table 4: University Malmquist Productivity and Component Changes

	Total	Technical	Efficiency	Management	Scale
Mean	0.987	1.003	0.984	0.987	0.997
Median	0.991	1.000	0.991	1.000	1.000
Minimum	0.856	0.925	0.886	0.886	0.898
Maximum	1.165	1.165	1.130	1.150	1.059
Standard Dev.	0.047	0.036	0.035	0.031	0.019
Percent less than 1.0	65%	50%	62%	50%	48%
Percent Efficient	5%	2%	18%	32%	21%
Percent Greater than 1.0	30%	48%	20%	19%	31%
Academic Year					
2006-07	0.973	1.003	0.97	0.984	0.986
2007-08	0.97	0.979	0.991	0.979	1.012
2008-09	1.015	1.026	0.99	0.996	0.993

Based on the average Malmquist index of 0.987, we are led to conclude that there occurred a slight regress in average university productivity over the four academic years. However, the distribution of university performances is fairly tight with a range of 0.856 to 1.165 and a standard deviation of only 0.047. It is encouraging that positive productivity gains surfaced among 30% of the universities and, based on the median index of 0.991, another 20% were reliably close to such achievement. Moreover, the annual changes show that the regress was confined to 2006-07 and 2007-8 and then followed by a substantial productivity increase in the 2008-09 academic year.

When the Malmquist index is decomposed, it can be generally concluded that movements toward productivity gains were occurring through technological changes brought about by shifts in university frontiers. However, that positive change amounted to only 0.3% on average and was more than offset by the decrease in technical efficiency: the mean index being 0.984 or approximately a 2% decline. Evidence of this is also apparent in that 50% of the universities experienced technological change through frontier shifts while 62% realized some deterioration in technical efficiency. Of course, 38% of universities were therefore able to consistently maintain (18%) their level of technical efficiency or improve (20%) upon it. Once again, examining the dynamics, the analysis uncovers a key technological improvement of 2.6% in the 2008-09 academic year but a laboring technical efficiency that persistently remains just below 100%.

In the final two columns of Table 4 the technical efficiency change is partitioned into that part that is due to pure or managerial technical efficiency and that part due to scale efficiency. The results indicate that 50% of the universities were managerially efficient (32%) or undertook measures that improved (19%) upon managerial efficiency in the allocation of resources. And although the index remained below a value of one each year, there was regularity in efficiency improvement in moving from 0.984 to 0.996. In the aggregate, however, there were the scale efficiency effects working against managerial efforts. Decreases in scale efficiency struck 48% of universities, again indicating that universities could have been overwhelmed with unexpected enrollment demands and subsequent credit hour production. Indeed, it is interesting that scale efficiency shows an improvement in the 2007-08 academic year (1.012) and then in the midst of the recession a relapse in the 2008-09 academic year (0.993).

It can also be useful to use DEA in examining performance of individual institutions. To that end, Appendix Table A.1. lists the individual universities according to their mean total factor productivity. The university's Malmquist productivity index is reported along with the rank that it achieved with respect to each of the four efficiency measures. On the basis of results, the rank correlation coefficients are provided at the end of the Table A.1. The strongest correlation between productivity change and efficiency change comes from management efficiency change (0.88). That suggests that managerial decision-making in the allocation of resources can be the largest contributor to university productivity gains. In obvious support of this relationship, one only needs to examine those universities that ranked lowest in productivity gains. They tend to also have the lowest rank in pure efficiency change. An anomaly is No.132 productivity ranked Louisiana Tech. That institution's poor technological and efficiency changes are likely to be the result of the long lasting effects of the 2005 devastation brought by Hurricane Katrina.

Scale effects have the weakest showing (0.42) in correlating with universities that achieved the largest productivity improvements. Similarly, the smallest correlation coefficient of 0.04 indicates that scale effects carry little to no influence on managerial efficiency; the top ranked universities in management efficiency do so despite any scale effects. A prime example is the No.1 productivity ranked Maryland-Baltimore with a corresponding pure efficiency rank of No.1 and a scale efficiency rank of No.110. Another is No.10 productivity ranked Ohio St. that carries a No.2 rank on the management front and a No.114 rank for scale efficiency change. Also to note is the negative correlation between university rank performance with respect to technological changes and efficiency changes. Indicative is No.2 productivity ranked Missouri-Kansas City with a No.1 efficiency change rank and a No. 47 technological change rank. Similarly, there is No.31 Purdue that generated a No. 6 efficiency rank and No.114 technological change rank. However, the impacts of these frontier and efficiency changes are positively correlated with total factor productivity. The rank order of university productivity improvements has a correlation of 0.58 and 0.62 with university technological and efficiency changes, respectively.

6 Conclusions

The objective of this paper was to apply the methodology offered by DEA to the investigation of operating efficiencies and productivity changes pertaining to U.S. research and doctoral universities. These top level universities represent the guiding forces in the U.S. system of public higher education. In the present paper, their efficiency in producing education and research is estimated using panel data spanning the 2005-09 academic years. The use of panel data also provided a much richer analysis of productivity changes over time using the Malmquist index. In total, the analysis provided estimates of university efficiency and productivity changes over a period of relative stability accompanied by economy wide growth followed by a period of international financial turmoil resulting in the so-called Great Recession.

The paper is believed to be the first research in providing DEA panel data efficiency and productivity estimates for U.S. universities. For universities in other countries, a literature search revealed only three other longitudinal DEA studies. Those studies found university productivity gains were, on average, positive but only 0.2% in the Philippines compared to 3.3% Australia. Gains were significantly more powerful in England and Italy at 8.5% and 9.4%, respectively. In contrast, for American universities, the present study suggests 2005-09 average productivity regress on the order of 1.3%. Of course, all three previous studies use academic years predating the global financial crisis and, therefore, unlike the present study could not account for the potential effects on university operations possibly imposed by it. However, when annual productivities are evaluated, there is even evidence of U.S. productivity declines beginning in the 2006-07 academic year, and therefore, preceding the financial crisis. But to their credit, U.S. universities partly compensate with productivity gains of 1.5% during the 2008-09 academic year and, therefore, in the midst of recession and widespread budget cuts accompanied by increased enrollment demands. Given the academic years under study, it is unknown as to what extent universities in those other countries mirrored the U.S. experience.

According to the present findings, productivity regress was accompanied by decreasing returns to scale that prevailed among more than half of the universities. However, from a policy perspective, one should not prescribe downsizing because the scale effects were likely generated by the increased enrollments and production of credit hours that occurred during the high unemployment years of the recession. Thus, those scale effects would have to be revisited with additional future years of data hopefully accompanied by an improved economy wide setting. Somewhat disturbing was the finding that efficiency changes due to university managerial decision tended to have a negative impact on productivity changes. On a positive note, that effect was weakened with each consecutive academic year as managerial efficiency progressed, albeit slightly. Thus, the productivity gain that developed during the last academic year was credited to technological changes in the delivery of U.S. higher education teaching and research. With these final remarks it is not possible to make comparisons with other studies due to the lack of consistency in reported results. And even with the limited availability of results, inter country comparisons are at best problematic owing to variations in modeling assumptions, output and input measures, and substantially different higher education regulatory and financial environments. That suggests a future research agenda that creates greater research uniformity in modeling approaches, thereby enabling the introduction of environmental controls and subsequent inter country comparisons and policy conclusions. That, of course, is a tall order given that it is also necessary to develop and make available a more internationally uniform data base pertaining to higher education systems and their individual institutions.

Appendix Productivity and Decomposition Rankings

Appendix Table A.1: Productivity and Component Decomposition Rankings

Productivity Index	University	Technical Rank	Efficiency Rank	MGT Rank	Scale Rank
1.165	Maryland-Baltimore	1	28	1	110
1.147	Missouri-Kansas Ct	47	1	27	1
1.095	Georgia St	2	29	3	29
1.087	SUNY-Albany	4	30	28	3
1.086	New Mexico IT	5	31	24	4
1.076	Washington	22	4	29	5
1.067	Colorado	7	32	30	6
1.059	Tennessee	32	9	5	70
1.052	Missouri-Columbia	15	18	6	42
1.047	Ohio St	10	27	2	114
1.045	Illinois-Urbana	88	2	22	10
1.038	Mid Tennessee	13	33	7	84
1.037	Wisconsin	27	20	8	77
1.034	Rhode Island	93	3	9	71
1.034	Florida	11	70	12	33
1.031	Cincinnati	85	5	31	11
1.028	Nevada-Vegas	42	21	10	81
1.027	Indiana-Purdue-IN	30	34	16	25
1.025	Virginia Polytech	31	52	23	17
1.023	Mass-Amherst	70	10	32	21
1.023	Arizona	46	22	13	85
1.021	New Hampshire	89	8	70	18
1.017	Utah	6	112	4	128
1.016	Mich-Ann Arbor	9	100	20	43
1.011	S Carolina	86	11	25	35
1.011	Central Florida	54	35	14	93
1.011	Illinois-Chicago	18	83	33	40
1.009	Akron	87	12	34	44
1.009	Georgia	16	92	35	45
1.008	Washington St	50	57	36	46
1.007	Purdue	114	6	37	47
1.006	SUNY-Buffalo	21	89	38	48
1.005	Nevada-Reno	51	66	39	49
1.004	Kansas St	59	54	40	50
1.004	S Florida	38	78	41	51
1.003	TX A&M -Commerce	61	36	42	52
1.003	Maryland-Coll Pk	56	61	43	53
1.003	Iowa	20	97	44	54
1.002	Colorado- Hlth Sci	64	37	45	55
1.002	S Dakota	35	81	46	56
1.002	Rutgers-Brunswick	26	93	47	57
1.000	Montana	103	14	48	58
1.000	N Carolina St	78	23	49	59
1.000	Georgia IT	66	38	50	60
1.000	Alabama-Birmingham	65	53	51	61
1.000	Wisconsin-Milwaukee	62	55	52	62

Appendix Table A.1: Continued

Productivity Index	University	Technical Rank	Efficiency Rank	MGT Rank	Scale Rank
1.000	Hawaii	55	71	53	63
1.000	Virginia Commonwealth	14	104	54	64
0.998	Indiana Pennsylvania	71	39	55	65
0.998	Maryland-Balt Co	44	82	56	66
0.997	E Tennessee St	73	40	57	67
0.994	E Carolina	122	7	15	101
0.994	Virginia	3	129	73	78
0.993	Clemson	112	13	91	14
0.993	S Dakota St	107	17	18	105
0.993	N Carolina-Greensboro	104	19	88	23
0.993	Wright St	28	103	60	91
0.992	Ball State	108	16	110	2
0.992	Indiana -Bloomington	48	84	86	27
0.991	Florida Atlantic	74	59	79	38
0.991	Arkansas	49	86	74	83
0.991	Louisville	23	105	71	89
0.989	S Illinois	43	99	85	36
0.988	Wyoming	53	87	61	99
0.987	SUNY Envir Sci	90	41	75	86
0.987	Bowling Green St	76	67	62	102
0.987	New Mexico	12	115	83	73
0.986	Oregon	101	25	97	12
0.986	Arizona St	80	63	80	87
0.986	Michigan St	75	68	19	121
0.986	Missouri-St Louis	77	69	104	9
0.985	Mississippi St	83	60	63	112
0.984	Nebraska	91	58	89	79
0.982	Indiana St	68	76	64	113
0.982	W Virginia	57	94	111	8
0.981	Southern Mississippi	119	15	94	30
0.980	Northern Illinois	98	56	81	100
0.979	San Diego St	106	42	11	131
0.977	Missouri-Rolla	110	26	98	24
0.976	George Mason	102	64	96	31
0.975	Kansas	84	77	87	98
0.974	Memphis	115	24	84	103
0.974	New Orleans	60	101	92	90
0.973	Arkansas-L Rock	105	65	65	122
0.973	Western Michigan	94	73	82	107
0.972	Alabama-Huntsville	113	43	72	115
0.970	Colorado St	96	75	26	124
0.970	N Dakota St.	92	79	76	116
0.970	Auburn	34	113	122	7
0.969	Montana St	24	118	69	123
0.968	Alabama	81	88	105	22
0.967	Oklahoma St	37	114	66	125
0.966	N Carolina	97	80	102	28

Appendix Table A.1: Continued.

Productivity Index	University	Technical Rank	Efficiency Rank	MGT Rank	Scale Rank
0.965	Kent St	95	85	67	126
0.965	N Dakota	52	109	108	20
0.965	Mississippi	25	120	99	74
0.965	Kentucky	17	123	100	80
0.963	Mass-Boston	117	44	106	37
0.961	Jackson St	120	45	109	32
0.959	Central Michigan	121	46	78	127
0.956	Wichita St	123	47	103	92
0.956	Stony Brook	72	107	117	19
0.954	Iowa St	33	124	113	39
0.951	Oklahoma-Norman	45	121	101	111
0.950	Idaho	67	110	112	68
0.948	Texas Tech	111	95	95	119
0.944	Utah St	82	111	125	15
0.941	Wayne St	29	126	126	16
0.940	Idaho St	99	108	107	108
0.939	Houston	69	119	114	88
0.936	Tennessee St	116	102	120	69
0.934	Vermont	128	48	121	41
0.934	Louisiana St	19	130	115	95
0.932	S Carolina St	130	49	123	75
0.930	New Jersey Inst Tech	124	96	128	34
0.928	Louisiana-Lafayette	131	50	93	132
0.927	Florida Intl	132	51	119	104
0.923	Maine	109	116	118	109
0.922	Illinois St	129	74	127	94
0.917	Florida St	41	131	124	117
0.910	Cleveland St	100	125	116	130
0.889	Texas AM-Kingsville	126	122	131	106
0.887	New Mexico St	133	106	130	118
0.880	Toledo	79	133	132	120
0.879	Texas Southern	118	128	129	129
0.858	Louisiana Tech	127	127	68	133
0.856	Alabama AM	125	132	133	76
Rank Correlation Coefficients					
	1.00				
	0.58	1.00			
	0.62	-0.18	1.00		
	0.88	0.49	0.54	1.00	
	0.42	0.22	0.32	0.04	1.00

References

[1] T. Agasisti and G. Johnes, Beyond frontiers: comparing the efficiency of higher education decision-making units across more than one country, *Education Economics*, **17**, (2009), 59-79.

[2] T. Ahn, A. Charnes and W.W. Cooper, Some statistical and DEA evaluations of relative efficiencies of public and private institutions of higher learning, *Socio-Economic Planning Sciences*, **22**, (1988), 259-269.

[3] D. Athanassopoulos and E. Shale, Assessing the comparative efficiency of higher education institutions in the UK by means of data envelopment analysis, *Education Economics*, **5**, (1997), 117-134.

[4] N.K. Avkiran, Investigating technical and scale efficiencies of Australian Universities through data envelopment analysis, *Socio-Economic Planning Sciences*, **35**, (2001), 57-80.

[5] R.D. Banke, A. Charnes and W.W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, **30**, (1984), 1078-1092.

[6] J.E. Beasley, Comparing university departments, *Omega*, **18**, (1990), 171-183.

[7] J.E. Beasley, Determining teaching and research efficiencies, *Journal of the Operational Research Society*, **46**, (1995), 441-452.

[8] T.M. Breu and R.L. Raab, Efficiency and perceived quality of the nation's 'top 25' National Universities and National Liberal Arts Colleges: An application of data envelopment analysis to higher education, *Socio –Economic Planning Sciences*, **28**, (1994), 33-45.

[9] B. Casu, and E. Thanassoulis, Evaluating cost efficiency in central administrative Services in UK universities, *Omega*, **34**, (2006), 417-426.

[10] M.C. Castano and E. Cabanda, Sources of efficiency and productivity growth in the Philippine state universities and colleges: a non-parametric approach, *International Business and Economics Research Journal*, **6**, (2007), 79-90.

[11] K. Chakraborty and J. Poggio, Efficiency and equity in school funding: A case study for Kansas, *International Advances in Economic Research*, **14**, (2008), 228-241.

[12] A. Charnes, W.W. Cooper and E. Rhodes, Measuring the efficiency of decision making units, *European Journal of Operational Research*, **2**, (1978), 25-444.

[13] A. Cobert, R.R. Levary and M.C. Shaner, Determining the relative efficiency of MBA programs using DEA, *European Journal of Operational Research*, **125**, (2000), 656-669.

[14] Tim Coelli, A guide to DEAP version 2.1: A data envelopment analysis, *Working Paper Center for Efficiency and Productivity Analysis*. Department of Economics, University of New England, (1996).

[15] E. Cohn, S.L. Rhine, W. Rhine and M.C. Santos, Institutions of higher education as multiproduct firms: Economies of scale and scope, *Review of*

Economics and Statistics, **71**, (1989), 284-290.
[16] W.D. Cook and J. Zhu, *Data Envelopment Analysis,* Wade D. Cook and Joe Zhu, (2008).
[17] W.W. Cooper, L.M. Seiford and J. Zhu, *Handbook on Data Envelopment Analysis,*Boston, Kluwer Academic Publishers, 2004.
[18] R. Fare, S. Grosskopf, M. Norris and Z. Zhang, Productivity growth, technical progress, and efficiency changes in industrialized countries, *American Economic Review*, **84**, (1994), 66-83.
[19] M.J. Farrell, The measurement of productive efficiency, *Journal of the Royal Statistical Society*, **A CXX, Part 3**, (1957), 253-290.
[20] J.C. Glass, G. McCallion, D.G. McKillop, S. Rasarantnam and K.S. Stringer, Implications of variant efficiency measures for policy evaluations in UK higher education, *Socio-Economic Planning Sciences*, **40**, (2006), 119-142.
[21] J. Johnes, *Efficiency measurement*,in G. Johnes and J. Johnes (eds.) *International Handbook on the Economics of Education*, Cheltenham, UK, Edward Elgar, 613-670, 2004.
[22] P. Korhonen, R. Tainio and J. Wallenius, Value efficiency analysis of academic research, *European Journal of Operational Research*, **130**, (2001), 121-132.
[23] R. Koshal and M. Koshal, Economies of scale and scope in higher education: A case of comprehensive universities, *Economics of Education Review*, **18**, (1999), 269-277.
[24] K.H. Leitner, J. Prikoszovits, M. Schaffhauser-Linzatti, R. Stowasser and K. Wagner, The impact of size and specialization on universities' department performance: a DEA analysis applied to Austrian universities, *Higher Education*, **53**, (2007), 517-538.
[25] P. Lenton, The cost structure of higher education in further education colleges in England, *Economics of Education Review*, **27**, (2008), 471-482.
[26] S. Malmquist, Index numbers and indifference surfaces, *Trabajos de Estatistica*, **4**, (1953), 209-242.
[27] M.L. McMillan and W.H. Chan, University efficiency: A comparison and consolidation of results from stochastic and non-stochastic methods, *Education Economics*, **14,** (2006), 1-30.
[28] G. Reichmann, Measuring university library efficiency using data envelopment analysis, *Libri*, **54**, (2004), 136-146.
[29] G.T. Sav, Higher education costs and scale and scope economies, *Applied Economics*, **36**, (2004), 607-614.
[30] G.T. Sav, Managing operating efficiencies of publicly owned universities: American university stochastic frontier estimates using panel data, *Advances in Management and Applied Economics*, **2**, (2012), 1-23.
[31] Z. Sinuany-Stern, A. Mehrez and A. Barboy, Academic departments efficiency via DEA, *Compters and Operations Research*, **21**, (1994), 543-556.

[32] C. Worthington and B.L. Lee, Efficiency, technology and productivity change in Australian universities, 1998-2003, *Economics of Education Review*, **27**, (2008), 285-298.